MSc. Thesis VIBOT

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Abstract

The abstract will go here....

Research is what I'm doing when I don't know what I'm doing....

Werner von Braun

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Any acknowledgements???

Chapter 1

Introduction

1.1 Why underwater?

Manhood has managed to conquer variety of environments. At some point, humans could walk on the moon, send expeditions to cold or remote areas in different corners of the planet. Sea-floor constitutes the largest part of Earth's surface.

1.1.1 Localization - Where the Robot Is?

One of the main capabilities of the autonomous underwater vehicle is knowing to localize itself within an environment. To estimate its metric position and orientation in three dimensional space. Knowing where it actually is enables further tasks such as path tracking or various manipulation tasks. Therefore, it has the same role as parts of the human brain devoted to navigation.

The main topic is localization of an underwater vehicle. Localization essentially deals with the problem of the estimation of the position of the vehicle. A tool to accomplish it is the sensor measurement. Main idea is to establish the matching between the sensor measurements and the map elements. This process is not straightforward since many conditions influence the performance, including the very starting point of the localization: whether we have some previous estimate on the position or not [13]. Localization can be carried through by analysing the pose possibilities and choosing the one that reaches better coherence between the measurements and the map. Such methods are Monte Carlo localization and Markov localization. The other approach, a set of hypotheses for coupling together the sensor measurements and the map features. These hypotheses are ranked depending on number of consistent matches where the one with highest ranking is defining the position. This can be a costly process, therefore a number of methods deals with optimization of it.

Chapter 2

Problem Definition

Robots including underwater robots are designed to help humans by replacing them or helping them in accomplishing certain task. It is essential for successful application of an underwater vehicle that the vehicle can accurately estimate its own position in the environment. First of all, it autonomously makes decisions that are influenced by position information. Second, usability and quality of the data corresponds to the precision of the localization.

With the discovery and the development of Global Positioning System (GPS), the issue of the localization of all robots operating on land or in the air was solved with the considerably cheap and reliable system. However, designers of those machines that operate underwater remain being in quest for the localization system of similar performance that would work in vast and different environment such as water.

Due to the absorbtion of radio frequencies in salt water, GPS signal is not available in sea depths, and radio localization which serves as standard "above the surface" cannot be used. Therefore, various methods are developed to establish the localization underwater. New ways of measuring the vehicle position have been used The aim of the thesis report is to

The improvement of sensor performance enabled their usage in localization. Different types of sensors are typically used and the role of mathematical algorithm such as Kalman filter or its variations is to combine together sensor measurements from all the different sources and make an optimal estimate of the vehicle state: its position and orientation.

The aim of the project is to implement and evaluate navigation algorithm for an underwater vehicle. Navigation, as introduced in literature, implies two capabilities [6]:

- localization - accurate determination of the vehicle position and velocity with respect to a known reference point
- planning and the execution of the movements between locations

The work presented in the thesis will emphasize the first capability. Moreover, the first capability is a necessary step in carrying out the second capability correctly. To accomplish the task, sensor information is integrated in calculations. The purpose is to calculate the vehicle position in every moment as accurately as possible. Mathematical tool that will integrate the measurements and establish the final estimate is well known Kalman filter [] algorithm. More details about Kalman filter in chapter .

It is important to mention that localization under water tends to be different challenge compared with the localization on land or in the air. Namely, the usage of GPS signal is limited since it is available only on water surface. Therefore, speed and heading information obtained from inertial navigation system (INS) sensors is used together with the mathematical model of the motion to calculate the position, orientation and velocity via dead reckoning. Such strategy eventually leads to progressive error since measurement errors are integrated each time. To overcome this, GPS information which gives absolute distance is used to make corrections. It updates the position information whenever available - either directly, if the vehicle is on the surface or using long baseline acoustic positioning (LBL).

Another obstacle in managing localization is water environment itself. Usage of sensors based on light transmission such as camera, is limited because environment is such that it deforms or decreases the signal. A useful tool to determine the distance or the speed in water is sound, a mechanical wave that does not severely depend on light conditions and moves faster in water.

Chapter 3

State of the art (or the Literature Review...?)

This chapter gives an overview of the methods and existing algorithms for underwater vehicle localization. Localization is influenced with the development and performance sensor devices. Sensors can be regarded as the tool for managing the localization. Faster they are, more accurate they are, localization has more chances to be better. Oceanographic community typically uses three different strategies to handle the navigation underwater [16]. Of course, they can be combined together, depending on purpose: (1) transponder networks on the seafloor (long baseline), (2) sip - underwater vehicle communication (short baseline), and (3) sensors mounted on the underwater vehicle that measure range and inertial motion. Each of the strategies is different in terms of accuracy, costr and complexity [5]. Chapter § 4 gives more insight into performance and cathegorization of each sensor device used for underwater vehicle navigation. Following paragraphs are revising the documented ways to process such sensor information in order to be able to estimate the position in the environment. We could describe localization as absolute or relative, depending on which reference system we use when obtaining measurements. Absolute localization takes environment as reference system while relative consider the vehicle itself to be the reference.

Underwater navigation is using several instrumentation methods to carry out the robot localization in the sea [16]. These include transponder networks placed on the bottom of the sea, tracking systems between the ship and the underwater vehicle, and sensoring devices that measure range and dynamics mounted on the vehicle itself. Each of the methods has advantages and disadvantages. Transponder network gives accurate position information, however using it means installing and calibrating additional equipment [5].

In existing survey on underwater vehicle navigation, Kingsey et al. [11] already give a summary presenting some methods used. As introduced in [11], current vehicle position is named navigation state - a vector where the vehicle is and how it is oriented in space. Localization simply means finding a way to estimate navigation state vector. Naturally, sensors provide the data for the estimation.

The most simple approach would be dead reckoning - to take the raw sensor measurements and use them directly or within a simple mathematical model that describes the vehicle dynamics. However, many techniques presented in literature utilize sensor data as supplementary information with the information from the kinematic model. Rough classification of the localization methods would categorize them on stochastic state estimators (Section 3.1), simultaneous localization and mapping approach (SLAM, Section 3.2 and localization based on deterministic observers [11]. On top of already mentioned methods, some other strategies such as cooperation for navigation are explored [1] in order to overcome the shortcomings of conventional navigation approach.

3.1 Stochastic state estimators

The name of such methods suggests that states are treated as ultimately having feature of randomness built-in - means being or having a random variable. That does not seem as a wrong conclusion after recognizing that state of a system, is seldom known precisely. It is the essential nature of the process or the instrument used for measuring or the estimation algorithm itself that fails at submitting utterly accurate data all the time. We could say that many phenomena are random till certain extent. Statistically speaking, estimation is a rule used to calculate an estimate of a variable of interest using the observed data. As it is the case with random variables, we can say that certain state has an expected value, and that such “randomness” can be expressed with the distribution formula, resulting in values such as mean and standard deviation that fully describe the distribution in concrete case of gaussian, for instance. This approach has been appied often in underwater navigation. Most notable stachastic state estimator is Kalman filter. Kalman filter is an unbiased, optimal estimator that in majority of the localization examples utilizes the kinematic model for making a prediction and, in genral, describes how the system states change. Kalman filter and the EKF treat random variable as it has gaussian distribution which introduces some special features. Chapter § refchap:kalman focuses more on Kalman filtering. In case of an underwater vehicle localization is accomplished using unbiased estimation such as Extended Kalman Filter (EKF) and number of works report on usage of different variations of Kalman filters for state estimation. Following paragraphs make an overview of various stochastic estimator usage with the objective of determining (estimating) values that represent system state - location of the robot in the environment.

Some available works have already delt with the issue of managing localization using Kalman filtering. Master thesis of Negneborn [12] gives a useful overview of the theoretical knowledge and surveys the utilization of Kalman filtering for localizing underwater vehicles.

3.1.1 Linear stochastic state estimators

Blain et al. [2] study the application of Kalman filter in navigation of an underwater vehicle used for water dam inspection focusing on merging position and velocity information. This algorithm uses acoustic positioning sensor together with the integration the measured DVL sensor velocities [2] to estimate the position. Several issues are delt with in their work.

Kalman filter output could be corrupted in situations when observations (sensor measurements) are subject to interruption or periodic stopping. Due to the fact that not all the sensors can be always available, it is usually necessary to be capable of adding or removing sensor observations from the system without changing the navigation algorithm.

Asynchronous data delivery in this particular case means that the DVL sensor provides data with higher rate [2]. Such obstacle was solved by switching to estimation procedure suitable for that particular sensor measurement scenario. This simply means that if the acoustic sensor and DVL sensor provide new measurement, Kalman filtering is used to carry out the fusion. Otherwise, pure DVL velocity measurement is just integarated to update the position, as dynamic model would suggest.

Delays in measurements are evident in case of acoustic measurements where the time of the measurement (timestamp) is current measurement time minus the time it took for the acoustic signal to arrive. To overcome this, position estimate between two acoustic measurements is memorized. Position is meanwhile updated by integrating the DVL data. The procedure consists of two stages: at first, we make a new position estimate obtaine by integrating veolcities from the new position estimate to the actual time - correction of the position estimate.

Drolet et al. [4] introduce a flexible localization strategy based on sensor fusion and usage of several Kalman filters arranged together in a bank. Each filter is reduced to express simple cinematic equation and processes one state - works in one dimension. Idea is to integrate together sensor measurements that arrive at different time moments from different sensors. Method takes asynchronous information from sensors, manages a filter switching process so that the most recent data is used to update those filters that can be updated with such measurement [4]. Such sensor fusion strategy is adaptable in terms of number of sensors so that the best is taken out from the available input data, more robust to data loss. Moreover, asynchronous inputs are allowed.

Di Massa et al. report usage of Kalman filter framework for slightly different concept of navigation that takes surrounding terrain as reference for esitmating the position of the sonar ("terrain-relative navigation"), [3]. In their work, sonar image is matched to the map using mean absolute difference (MAD) as the matching criterion. Matching map location is considered as measurement of vehicle position [3]. Several matchings are selected and weighted depending on how much they relate to the terrain images. Weights correspond to uncertainties in estimation theory. Quality of similarity is used to weight each measurement. Solution consists of having resulting best estimate of location [3]. Information from selected matches is combined to make the best estimate. The role of Kalman filter framework is to carry out the estimation. Each of the chosen mathes is considered as one measurement together with its weight as uncertainty. The filtered state is the position of the image within the map.

Gade and Jalving introduce aided post processing navigation system deployed on a commercial underwater vehicle [7]. Idea is that vehicle records sensor data while accomplishing mission under the sea surface. At the same time, a vessel is positioned on the surface recieving information of its position through the reliable Differential Global Positioning System (DGPS). After the mission is over, data are combined together with position data that was simultaneously recorded on the survey vessel located on the surface. Kalman filtering is used when merging the data. *Error-state* Kalman filter is used to combine sensor measurements and their error models. Observations in case of such filter is the difference between measured and computed values. Instead of working directly with states, presented algorithm filters the errors, so that the ultimate position and heading estimate can be derived by subtracting the estimated erros from, as authors suggest, corresponding calculated state elements. This way, final aim of obtaining vehicle position and heading together with the accuracy of such estimate [7].

Dissertation [15] gives the suggestion how to improve the vehicle position estimation when reconstructing maps of the sea floor. Visual information of the terrain is used as the feedback that makes terrain mapping data and the vehicle navigation data more consistent. Inspiration for investigating lies in fact that map-making depends on localization quality. Navigation errors are potentially large scale particularly seriously affecting the results when mapping is vehicle-based [15]. Existing local navigation is used together with terain-relative measurements. Namely, terrain sub-maps are created over short periods while the vehicle works out the innacurate localization using dead reckoning. Sub-maps are registered resulting in position measurements between two vehicle states, placing an additional constraint on the vehicle positon estimates. Delayed EKF is used to merge together the measurements ("sub-map" registrations and previously reached vehicle locations) into the navigation framework. Delayed state version of the recursive EKF enables retaining knowledge of prior platform positions.

Yun et al. introduce and present simulation and testing results of the navigation system that combines the usage of inertial measurement unit together with GPS fixes that occur less frequent and asynchronously [17]. Asynchronous Kalman filter with six states for orientation and eight states for position estimation is implemented [17]. Process model takes the velocities and GPS bias, models them as white noises passed through the first order systems with the time constant. Measurement consists of synchronous velocity measurements and asynchronous DGPS information. The design of the filter for the position estimation algorithm conforms to the standard routine, with the difference that the measurement vector has different length depending on the number of available valid sensor inputs, hence it has a flexible size, but each observation updates the state vector of the fixed size [17]. The idea of the asynchronism is that DGPS signals are used, if available and as soon as they are available, together with the speed measurements. This way, the localization algorithm uses the most of the data that are currently available.

The usage of the stochastic estimators implies having a known model that describes system state transiton from one moment to another (plant model) and model that desribes transiton from state to the measurement (observation model). Such model does not have to be the same each time. Jakuba and Yoerger [9] study the way to optimize navigation by estimating the vehicle model parameters, for instance various dynamics or buoyancy coefficients that normally influence the model, but are treated as constant. Their study involves postprocessing of the navigation data and heuristic estimate of these coefficients' optimal value. Real missions that applied the technique resulted in reduced noise in localization data, therefore giving clearer tracking.

3.1.2 Nonlinear stochastic state estimators

The issue of linearizing or nonlinearizing of the plant and observation models within filters was introduced in chapter on filtering, § refchap:kalman. Various works report the usage of nonlinear estimators such as Unscented Kalman Filters (UKF). Methods that are based on random sampling ("Monte Carlo methods"), for instance Particle Filters (PF), are also used for localization, which brings us back to the concept of stochasic value, but from different perspective this time.

Julier and Uhlmann introduce the method that carries out nonlinear filtering [10]. It is an alternative generalization of the KF that changes the approach of representing mean and variance of the random variable. Their research is a quite useful and comprehensive theoretical overview of filtering in general and the role of Extended Kalman Filter (EKF) in switching to nonlinearity world. Introduced filter, later known as Unscented Kalman Filter (UKF) is regarded as more precise alternative to EKF that is, in addition, easy for implementation.

3.2 Terrain-aided navigation

Eustice et al. address the problem of precise localization as a prerequisite for high resolution underwater imaging of large objects placed on the sea-bed [5]. Precise navigation would enable decent coverage of the spatious site of interest which is mission task. Proposed solution uses a vision-based SLAM approach together with vehicle's inertial measurements. !! This paper is not entirely clear !!

3.3 Deterministic state estimators

3.4 Cooperation for navigation

The dissertation of A. Bahr ([1]) proposes an algorithm particularly suited to the underwater environment. Cooperation in navigation is already available in air or the surface of the Earth. The work focuses on cooperative localization where group of vehicles communicate between each other to accomplish cooperative localization. Stated advantages of such approach is that, apart from having more than one vehicle, no additional infrastructure is necessary [1]. Everything comes down to the usual sensor and communication package already available on vehicles [1].

Chapter 4

Sensors overview

This chapter gives an overview of the sensors used in localization of an underwater vehicle. Underwater positioning can be based on different methods. Hence, it is possible to distinct localization that uses fixed, ground based reference, and relative positioning based on velocity integration.

4.1 Inertial navigation system

Provides position, linear velocities, orientation and angular velocitioes. Accelerations are not used.

4.2 Acoustic system

Provides the absolute position, ground based refernce. Principal way of exchanging the information through the environment is sound - therefore acoustic. Long baseline(LBL) is used for measuring position with respect to several tethered beacons placed in water. It can be understood as the extension of the GPS underwater. Such system uses acoustic signals to measure the distances. Vehicle uses the acoustic transponder to send the acoustic wave ("pinging"). The wave reaches beacon and reflects back to the vehicle. It consists of transceiver and array arranged collection of beacons: LBL transceiver pings each of the beacons, detects the signal travel time and

4.3 Bathymetry system

Accomplishes depth measurement. It is possible to use acoustic system for this purpose, however, bathymeter using pressure information tends to be more precise and trustable.

As stated in some practical implementations ([2]), DVL and acoustic sensor perform

- **DVL** - measures velocities
- **COMPASS** - measures heading
- **MRU** - in some robots used to measure roll and pitch

Chapter 5

Kalman filtering

5.1 Linear filtering

Idea is that the system can be described with set of states that evolve in time. There can be various number of states and all of them are grouped together in the state vector. Navigation system could, for instance, group together position coordinates and orientation angles in the state vector. If the system is considered as discrete, transition from one discrete value of the state vector to the next one, is described with the function f called process model, equation 5.1, where the current state, $x(k+1)$, is calculated using the process model with prevoius state ($x(k)$), current input ($u(k+1)$) and process noise ($v(k+1)$) as arguments. In other words, model mathematically describes how the state changes for a given input. System formula 5.1 is used as first stage of filtering.

$$\boldsymbol{x}(k+1) = \boldsymbol{f}[\boldsymbol{x}(k), \boldsymbol{u}(k+1), \boldsymbol{v}(k+1), k+1] \tag{5.1}$$

Thus, our system is not entirely an unknown black box once a linear Kalman Filter(KF) is attached to it. A hint about its dynamics is known in form of process model. The only information available once the filtering starts, are its control inputs (u) and a set of observations (z). equation 5.2 associates observations with the state. Similarly as shown in 5.1, x and u present the state, while w represents the additive measurment noise and function h observation model [10].

$$\boldsymbol{z}(k+1) = \boldsymbol{h}[\boldsymbol{x}(k+1), \boldsymbol{u}(k+1), k+1] + \boldsymbol{w}(k+1) \tag{5.2}$$

Assumptions that KF uses:

- distribution of a random variable is assumed to be Gaussian, therefore mean and variance can fully describe it
- linear transform of a Gaussian distribution gives another Gaussian distribution

In spirit of that, noise vectors and thus linearly derivated state and observation vectors are Gaussian. Another assumption is that noise vectors v, w have zero mean values and that their elemets are not correlated, which was stated in equations 5.3.

$$\begin{aligned} E\left[\boldsymbol{v}(i)\boldsymbol{v}^T(j)\right] &= \delta_{ij}\boldsymbol{Q}(i) \\ E\left[\boldsymbol{w}(i)\boldsymbol{w}^T(j)\right] &= \delta_{ij}\boldsymbol{R}(i) \\ E\left[\boldsymbol{v}(i)\boldsymbol{w}^T(j)\right] &= \mathbf{0}, \forall i, j \end{aligned} \tag{5.3}$$

Kalman filter is a well known algorithm, covered in various literature [8], [14]. Discrete Kalman Filter is an optimal estimator in terms of minimizing mean squared error. It is an estimation process that works recursively, through iterations as shown in figure 5.1. One iteration uses equation 5.2. Each time One of its particularly useful features is the ability to combine together sensor measurements in mathematical form such that the solution is best possible estimate of the mean and the variance.

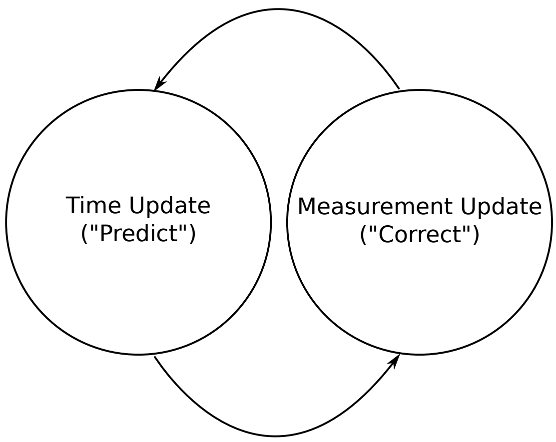

Figure 5.1: .

Kalman filter uses three basic stages: prediction measurement and update. This would mean that the mean and the variance of the state are measureable. Prediction in case of moving vehicle is calculated based on previous vehicle location and dead reckoning.

Kalman gain determines the relationship between the importance of each previous estimation () and the current measurement (). Essentially - it expresses how much we trust in the measurement with respect to what we prediceted. According to the formula (), it is determined by matrices Q and R which represent process noise covariance and the measurement noise covariance (uncertainty), respectively. It takes values between 0 and 1 with 0 meaning that we use estimation only and give no importance to the measurement, and 1 that we consider direct measurement as the only important one.

5.2 Extended Kalman Filter (EKF)

Real world models are rarely linear. The motiv for developing the Extended Kalman Filter is the adaptation of the linear Kalman Filter to dealing with nonlinear problems.

5.3 Unscented Kalman Filter (UKF)

Appendix A

The first appendix

If you need to add any appendix, do it here... Etc.

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